Neural-Symbolic Models for Logical Queries on **Knowledge Graphs**

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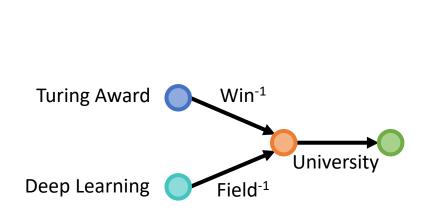


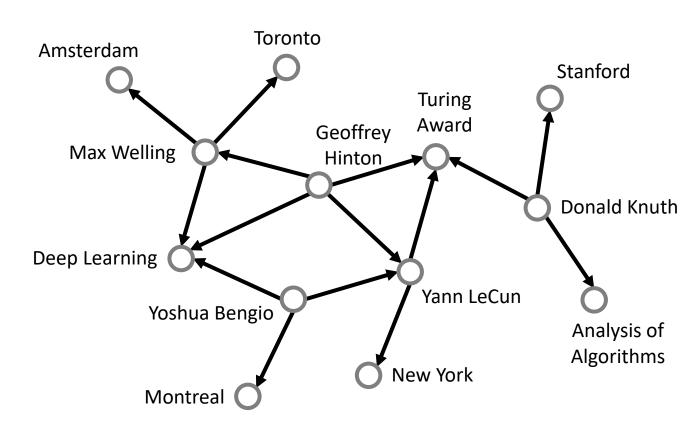




First-Order Logic Queries

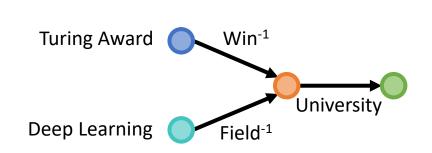
Which universities do the Turing Award winners of deep learning work in?

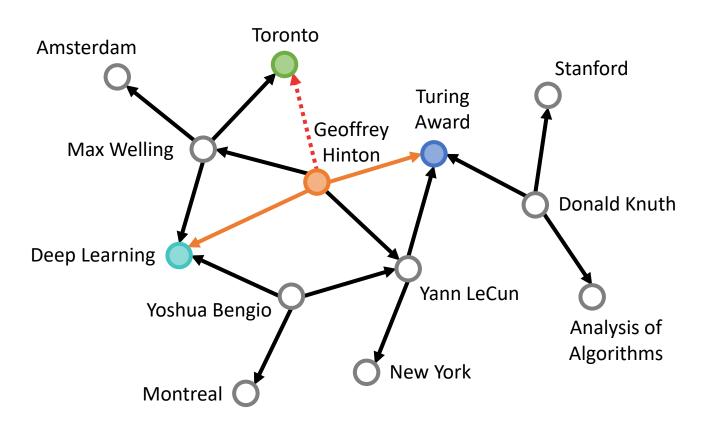




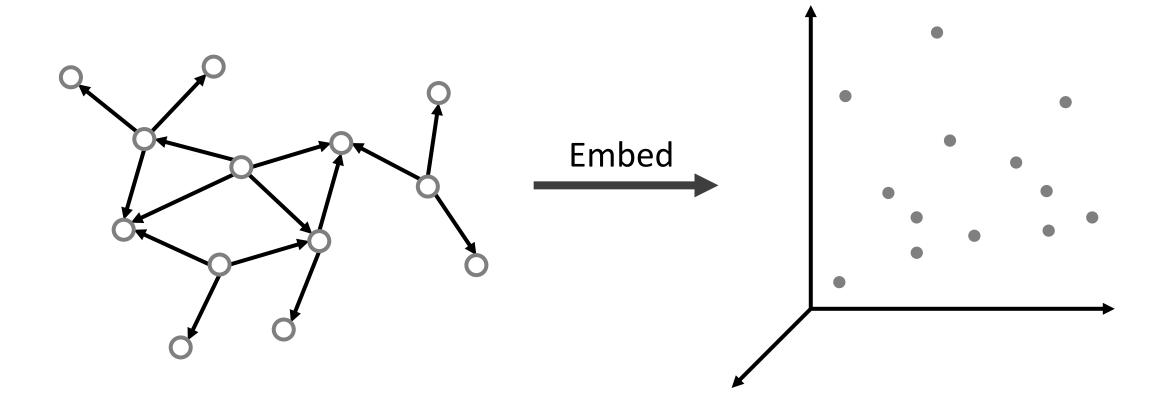
Symbolic Methods

Can't deal with missing links



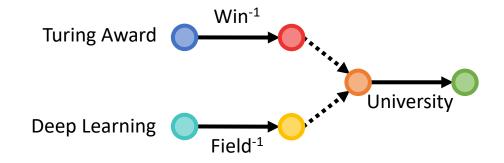


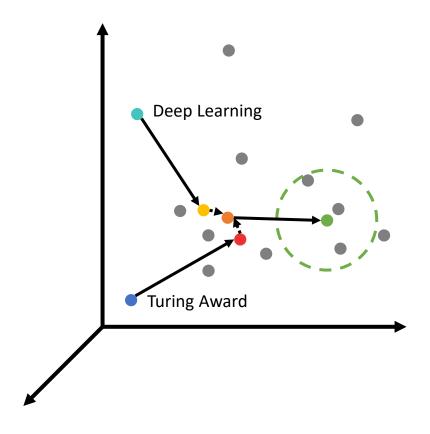
Neural Methods



Neural Methods

Can't interpret intermediate variables





Goal

Can we answer logical queries on incomplete knowledge graphs, with interpretability for intermediate variables?

Graph Neural Network - Query Executor (GNN-QE)

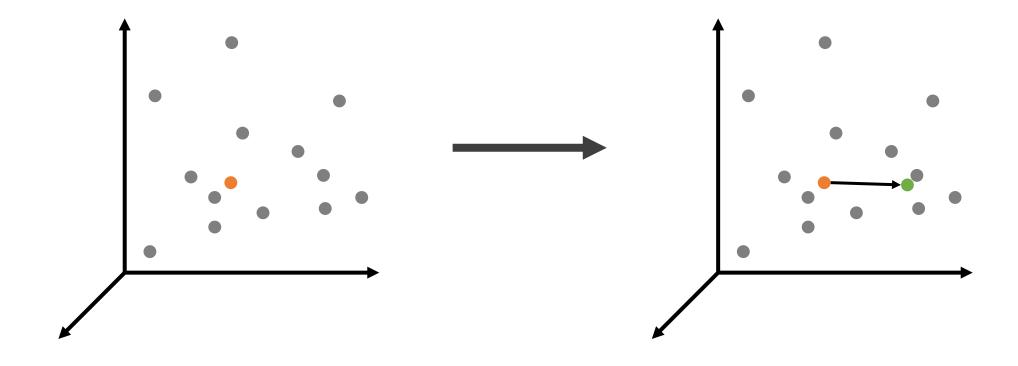
Neural + Symbolic

Symbolic: Decompose a logical query as operations over fuzzy sets

Neural: Learn relation projection operation with a graph neural network

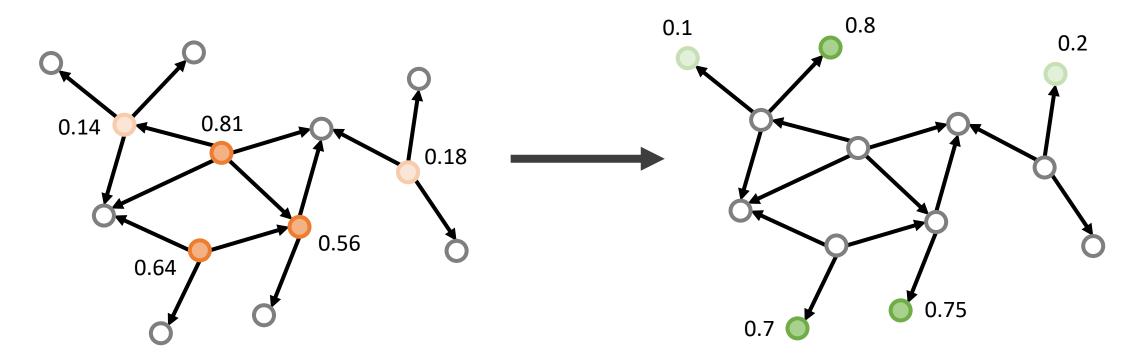
Operations over Embeddings

$$y = University(x)$$



Operations over Fuzzy Sets

y = University(x)



Four Operations

Relation Projection: University(x)

Conjunction: $x \land y$

Disjunction: $x \lor y$

Negation: $\neg x$

Four Operations

Relation Projection: University(x)

Conjunction: $x \land y$

Disjunction: $x \lor y$

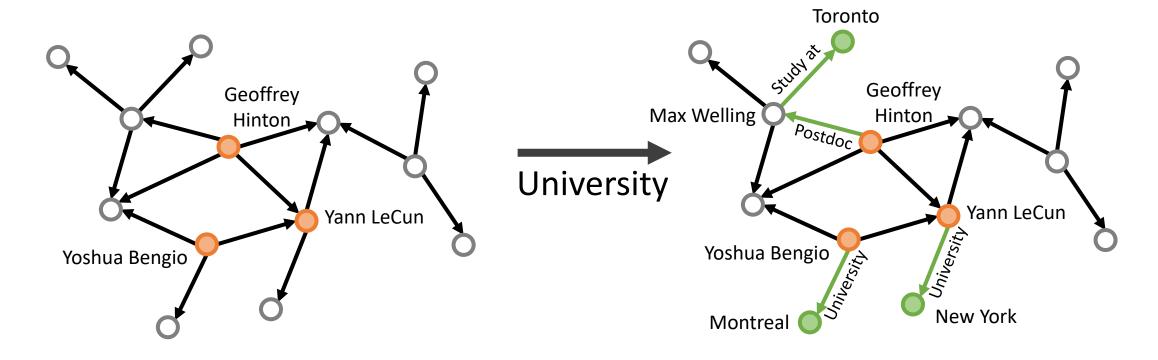
Negation: $\neg x$

Fuzzy Logic

GNN

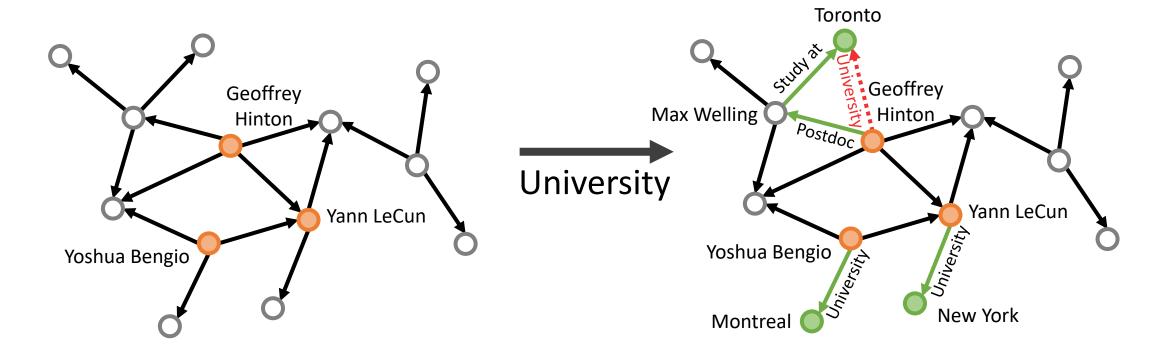
Relation Projection

Propagate with a GNN

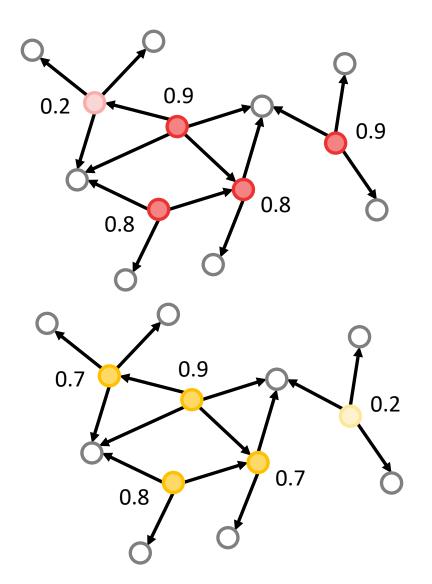


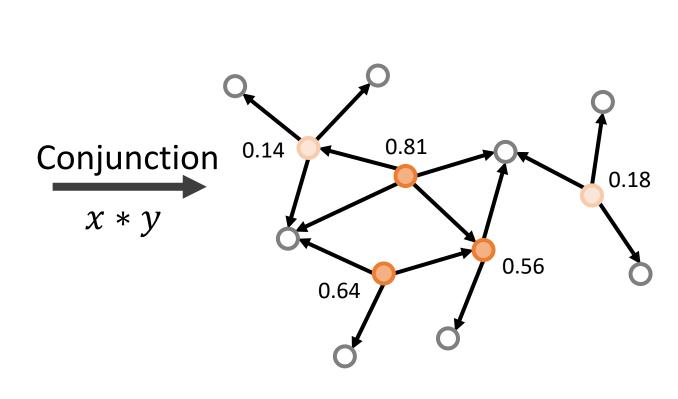
Relation Projection

Can deal with missing links



Fuzzy Logic Operations





Summary

22.3% relative improvement on EPFO queries 95.1% relative improvement on negation queries Interpret intermediate variables Predict the number of answers without explicit supervision